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Efficient aerodynamic design through evolutionary programming and support vector regression algorithms

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ABSTRACT

The shortening of the design cycle and the increase of the performance are nowadays the main challenges in aerodynamic design. The use of evolutionary algorithms (EAs) seems to be appropriate in a preliminary phase, due to their ability to broadly explore the design space and obtain global optima. Evolutionary algorithms have been hybridized with metamodels (or surrogate models) in several works published in the last years, in order to substitute expensive computational fluid dynamics (CFD) simulations. In this paper, an advanced approach for the aerodynamic optimization of aeronautical wing profiles is proposed, consisting of an evolutionary programming algorithm hybridized with a support vector regression algorithm (SVMr) as a metamodel. Specific issues as precision, dataset training size and feasibility of the complete approach are discussed and the potential of global optimization methods (enhanced by metamodels) to achieve innovative shapes that would not be achieved with traditional methods is assessed.

1. Introduction

The challenges of the aeronautical industry in the near future will require new computational tools for the design of the type of aircraft that will be demanded by the European industry, according to the guidelines stated at the ACARE 2020 (Argüelles et al., 2001) and 2050 (ACARE Advisory Council for Aeronautics Research in Europe, 2010) flight paths. The aeronautical industry agrees that these objectives make necessary the design of an innovative aircraft shape rather than further local improvements in the traditional wing-body-tail configuration. Efficient and accurate shape design optimization tools, able to consider novel concepts through the use of flexible geometry parametrization, are becoming a must for the aeronautical industry.

The aerodynamic design problem can be solved using either deterministic or non deterministic methods. Deterministic approaches often require the gradient information of the objective function. These gradient-based methods have been broadly used but they need a continuous evaluation function and have a weak performance in a noisy environment. In addition, they are strongly dependent on the initial configuration and could get trapped into a local minimum. On the other hand, non-deterministic methods such as evolutionary algorithms (EAs) have the ability to work with noisy objective functions, without assumptions on continuity (Lian, Oyama, & Liou, 2010). They also have a high potential to find the global optimum of complex problems involving a large amount of design parameters. However, they require a vast number of evaluations to obtain the optimum solution, even for a small number of design variables.

In the case of aerodynamic design, each evaluation of an individual in the EA requires a complete CFD analysis which makes the method unfeasible, in terms of computational cost. To overcome this problem there are different approaches in the literature, such as the use of powerful processing machines, such as Graphic Processing Units (Kampolis, Trompoukis, Asouti, & Giannakoglou, 2010) or, more frequently, the use surrogate models or metamodels (Giannakoglou, 2002; Jin, 2005; Newman, Taylor, Barnwell, Newman, & Hou, 1999; Zhong-Hua, Zimmermann, & Görtz, 2010). A metamodel is an inexpensive and approximated model of a costly evaluation method. Regarding the aerodynamic design using EAs, the metamodel technique could be used to calculate the fitness of the candidate solutions by replacing the time demanding CFD tools, as previously shown in the literature (Giannakoglou, Papadimitriou, & Kampolis, 2006; Liakopoulos, Kampolis, Giannakoglou, & enabled, 2008). For this purpose, regressors based on neural computation could be used as metamodels, once they have been trained based on previous evaluations.

There are well-documented examples of the applicability of soft-computing approaches (neural networks and evolutionary-based techniques) in a broad range of prediction and optimization problems including some parts of aerodynamic or multidisciplinary optimization processes. The majority of published studies uses some type of evolutionary algorithms hybridized with neural

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networks as metamodels: in Giannakoglou et al. (2006) a complete study of different types of neural networks working as metamodels in an aerodynamic shape design problem is carried out. The study includes multilayer perceptrons and radial basis functions networks. In Liakopoulos et al. (2008) a grid-based hierarchical evolutionary algorithm hybridized with a radial basis function network is proposed also in different parts of aerodynamic design problems. There are more recent works discussing different aspect of hybridizing evolutionary algorithms and neural networks as metamodels for airfoil design (Asouti & Giannakoglou, 2009; Bompard, Peter, & Desideri, 2010; Cohen, Siegel, Seidel, Aradag, & McLaughlin, 2012; Santos, De Mattos, & Girardi, 2008; Di Stefano & Di Angelo, 2003). Other perspectives of the problem are also discussed in the literature, such as in Jahangirian and Shahrokhi (2011), where an approach based on evolutionary algorithms directly hybridized with an unstructured CFD solver and a neural network (multi-layer perceptron) as metamodel for the first step of the approach is proposed. Other authors have tested the performance of alternative evolutionary approaches such as particle swarm optimization (Khurana, Winarto, & Sinha, 2009; Praveen & Duvigneau, 2009). There are also alternative methods applied to aerodynamic shape design, such as fuzzy logic approaches (Hossain, Rahmanb, Hossen c, Iqbal, & Zahirul, 2011), multiobjective algorithms (Kampolis & Giannakoglou, 2008), works involving cokriging techniques (Zhong-Hua et al., 2010), and papers that describe computation frameworks developed to enhance the design process (Kim et al., 2009).

This work focuses on the first phase of the aerodynamic design process, i.e., obtaining an approximation to the best candidate from a broad design space (dataset of different geometries, including unconventional ones). The aim of this paper is to study the performance of an evolutionary programming approach hybridized with a support vector regression algorithm as metamodel in a problem of optimal airfoil design. To our knowledge, this important regression technique has not been extensively applied to aerodynamic design, and may have important advantages over previously mentioned metamodels, such as neural networks. It will be showed that the proposed approach is able to obtain accurate first airfoil designs which can be used, at a later stage, as input for a detailed design process using methods which requires more computational resources, such as CFD.

This paper is structured as follows: next section describes the proposed hybrid evolutionary programming – SVMr approach, giving details on the EP and SVMr algorithms. Then, the experimental part of the paper is explained, where different results on the SVMr performance as a metamodel are displayed. Finally, some final remarks on the feasibility of the proposed approach in case of industrial configurations are outlined.

2. Proposed approach

The process of the proposed approach is shown in Fig. 1. The objective is the shortening of the design cycle through a combined approach, where the fist stage makes use of evolutionary algorithms together with metamodels to estimate the aerodynamic data. In this phase, the inputs to the process are the target design point (flow conditions), the objective function and the constraints. The output is an approximation to the global optimal solution. As evolutionary algorithm, an evolutionary programming approach (Yao, Liu, & Lin, 1999) is proposed, which will evolve different airfoil geometries, in terms of an objective function, given by the metamodel. The use of a support vector regression (SVMr) is proposed to this end. In this section, the EP algorithm used to tackle the optimal evolution of airfoil geometries is explained, together with a detailed description of the EP encoding and the SVMr, which will be applied to obtain the aerodynamic coefficients associated to each geometry, in a fast and accurate way.

2.1. EP encoding: airfoil parametrization

Sobieczky parametrization (Li, Seebass, & Sobieczky, 1998) is used, which can represent a wide variety of airfoils with a reasonable number of parameters. This parametrization employs mathematical expressions for the proper representation of generic airfoil geometry (shape functions). This is accomplished by the use of polynomial functions for the airfoil thickness (y_t) and camber (y_c) lines:

$$y_t = a_1\sqrt{(x)} + a_2x + a_3x^2 + a_4x^3 + a_5x^4 \tag{1}$$

$$y_c = b_1x + b_2x^2 + b_3x^3 + b_4x^4 + b_5x^5 + b_6x^6 \tag{2}$$

The upper-and lower-side y-coordinates at a given chord location are given by:

$$y_u = y_t + y_c \tag{3}$$

$$y_l = y_t - y_c \tag{4}$$

The geometric parameters defining the airfoil are: position of the leading edge control point, position and airfoil maximum thickness, trailing edge thickness line angle, trailing edge thickness, leading edge camber line angle, camber at maximum thickness, position and maximum camber, camber at maximum thickness, trailing edge camber line angle and trailing edge camber. Fig. 2 shows the parameters used for airfoil definition. Note that the mean curvature line (colored in red) has been multiplied by 10 only for representation purpose.

It is possible to link a_n and b_n coefficients in Eqs. (1) and (2) to the geometric variables described in Table 1 as it is shown below. Using this parametrization, an airfoil shape is defined by basic geometric parameters, instead of the coefficient of shape functions directly. This provides more knowledge about the flow around the airfoil and therefore, about the aerodynamic performance.

To obtain the a_n coefficients related to thickness distribution Eqs. (5)–(9) are used:

$$0 = \frac{a_1}{2\sqrt{(xtth)}} + a_2 + 2a_3xtth + 3a_4(xtth)^2 + 4a_5(xtth)^3 \tag{5}$$

$$ytth = a_1\sqrt{(xtth)} + a_2xtth + a_3(xtth)^2 + a_4(xtth)^3 + a_5(xtth)^4 \tag{6}$$

$$atte = \frac{a_1}{2} + a_2 + 2a_3 + 3a_4 + 4a_5 \tag{7}$$

$$ytte = a_1 + a_2 + a_3 + a_4 + a_5 \tag{8}$$

$$ytle = a_1\sqrt{(xtle)} + a_2xtle + a_3(xtle)^2 + a_4(xtle)^3 + a_5(xtle)^4 \tag{9}$$

Eqs. (10)–(14) are used to compute the b_n coefficients for camber:

$$acle = b_1 \tag{10}$$

$$ycth = b_1xtth + b_2(xtth)^2 + b_3(xtth)^3 + b_4(xtth)^4 + b_5(xtth)^5 + b_6(xtth)^6 \tag{11}$$

$$0 = b_1 + 2b_2xcmc + 3b_3(xcmc)^2 + 4b_4(xcmc)^3 + 5b_5(xcmc)^4 + 6b_6(xcmc)^5 \tag{12}$$

$$acte = b_1 + 2b_2 + 3b_3 + 4b_4 + 5b_5 + 6b_6 \tag{13}$$

$$ycte = b_1 + b_2 + b_3 + b_4 + b_5 + b_6 \tag{14}$$

The geometries used for training and validation, are generated from variation of these design variables, within the considered ranges displayed in Table 1. As it can be observed in the table, the leading edge control point, the trailing edge thickness and the trailing edge camber are maintained constant in order to compare the results with previous work (Santos et al., 2008). Therefore, two or three values in the range of each of the remaining eight geometric variables are used to generate the database of 5000 geometries. Fig. 3(a) shows the airfoils defined by the minimum, maximum and averaged value in each of the geometric variables. A huge set of airfoils are included in the database in order to exploit the